Detection of independent functional networks during music listening using electroencephalogram and sLORETA-ICA

Jäncke, Lutz ; Alahmadi, Nsreen

Abstract: The measurement of brain activation during music listening is a topic that is attracting increased attention from many researchers. Because of their high spatial accuracy, functional MRI measurements are often used for measuring brain activation in the context of music listening. However, this technique faces the issues of contaminating scanner noise and an uncomfortable experimental environment. Electroencephalogram (EEG), however, is a neural registration technique that allows the measurement of neurophysiological activation in silent and more comfortable experimental environments. Thus, it is optimal for recording brain activations during pleasant music stimulation. Using a new mathematical approach to calculate intracortical independent components (sLORETA-IC) on the basis of scalp-recorded EEG, we identified specific intracortical independent components during listening of a musical piece and scales, which differ substantially from intracortical independent components calculated from the resting state EEG. Most intracortical independent components are located bilaterally in perisylvian brain areas known to be involved in auditory processing and specifically in music perception. Some intracortical independent components differ between the music and scale listening conditions. The most prominent difference is found in the anterior part of the perisylvian brain region, with stronger activations seen in the left-sided anterior perisylvian regions during music listening, most likely indicating semantic processing during music listening. A further finding is that the intracortical independent components obtained for the music and scale listening are most prominent in higher frequency bands (e.g. beta-2 and beta-3), whereas the resting state intracortical independent components are active in lower frequency bands (alpha-1 and theta). This new technique for calculating intracortical independent components is able to differentiate independent neural networks associated with music and scale listening. Thus, this tool offers new opportunities for studying neural activations during music listening using the silent and more convenient EEG technology

DOI: https://doi.org/10.1097/WNR.0000000000000563

Originally published at:
Jäncke, Lutz; Alahmadi, Nsreen (2016). Detection of independent functional networks during music listening using electroencephalogram and sLORETA-ICA. NeuroReport, 27(6):455-461.
DOI: https://doi.org/10.1097/WNR.0000000000000563

Detection of independent functional networks during music listening using electroencephalogram and sLORETA-ICA

Lutz Jäncke[a,b] and Nsreen Alahmadi[b]

The measurement of brain activation during music listening is a topic that is attracting increased attention from many researchers. Because of their high spatial accuracy, functional MRI measurements are often used for measuring brain activation in the context of music listening. However, this technique faces the issues of contaminating scanner noise and an uncomfortable experimental environment. Electroencephalogram (EEG), however, is a neural registration technique that allows the measurement of neurophysiological activation in silent and more comfortable experimental environments. Thus, it is optimal for recording brain activations during pleasant music stimulation. Using a new mathematical approach to calculate intracortical independent components (sLORETA-IC) on the basis of scalp-recorded EEG, we identified specific intracortical independent components during listening of a musical piece and scales, which differ substantially from intracortical independent components calculated from the resting state EEG. Most intracortical independent components are located bilaterally in perisylvian brain areas known to be involved in auditory processing and specifically in music perception. Some intracortical independent components differ between the music and scale listening conditions. The most prominent difference is found in the anterior part of the perisylvian brain region, with stronger activations seen in the left-sided anterior perisylvian regions during music listening, most likely indicating semantic processing during music listening. A further finding is that the intracortical independent components obtained for the music and scale listening are most prominent in higher frequency bands (e.g. beta-2 and beta-3), whereas the resting state intracortical independent components are active in lower frequency bands (alpha-1 and theta). This new technique for calculating intracortical independent components is able to differentiate independent neural networks associated with music and scale listening. Thus, this tool offers new opportunities for studying neural activations during music listening using the silent and more convenient EEG technology. ***NeuroReport*** **27:455–461 Copyright © 2016 Wolters Kluwer Health, Inc. All rights reserved.**

NeuroReport 2016, **27**:455–461

Keywords: electroencephalogram, independent components, music listening, scale listening, sLORETA, sLORETA-IC

[a]Department of Neuropsychology, Psychological Institute, University of Zurich, Zurich, Switzerland and [b]Department of Special Education, Program of Higher Educational Studies, King Abdulaziz University, Jeddah, Saudi Arabia

Correspondence to Lutz Jäncke, PhD, Division Neuropsychology, Institute of Psychology, University of Zurich, Binzmuehlestrasse 14, PO Box 25, CH-8050 Zurich, Switzerland
Tel: +41 446 357 557; fax: +41 446 357 409/+41 446 357 400;
e-mail: lutz.jaencke@uzh.ch

Received 19 January 2016 **accepted** 11 February 2016

Introduction

Identifying the neural networks associated with music perception has become a topic of great interest in cognitive neuroscience. In this context, many published studies have used functional MRI (fMRI) to delineate the neural underpinnings of music perception [1–10]. In general, these studies have shown that the limbic system as well as cortical areas outside the auditory areas (e.g. the parietal and frontal cortices) is strongly bilaterally activated when listening to musical pieces. Although fMRI provides good spatial resolution for localizing hemodynamic responses, its measurements are partly problematic when examining brain activations during music stimulation due to scanner noise [11] and the somewhat uncomfortable experimental environment [12].

Thus, when studying neural responses to auditory stimuli in general and music stimuli in particular, one should use a neurophysiological technique that allows the presentation of auditory stimuli (e.g. music) in a silent and more convenient experimental setting. As such, electroencephalogram (EEG) and magnetoencephalography (MEG) seemed to be better suited for registering neural responses to auditory stimuli. This holds especially true for experiments studying neural responses to music stimuli, as the perception of musical pieces are associated with emotional and esthetic reactions, which are most likely negatively influenced by background scanner noise, even if the intensity of the background noise is substantially diminished.

One major drawback of the EEG and MEG techniques is the lower spatial resolution for identifying the intracortical sources on the basis of the scalp distribution of EEG/MEG activity and the available mathematical procedures for estimating the inverse solutions. However, these mathematical techniques are becoming more sophisticated, thus improving the 'inverse solutions' substantially. A general rule is that the spatial precision of these 'inverse solutions' increases with the number of

 DOI: 10.1097/WNR.0000000000000563

electrodes (or sensors for MEG) used [13,14]. However, it has also been shown that good solutions can be achieved even with relatively few electrodes (e.g. 19 or 32 electrodes) when the signal-to-noise ratio is very good [15–18]. One possibility for increasing the signal-to-noise ratio is to increase the number of EEG segments or to use averaged and filtered EEG signals for estimating the intracortical sources. It is also useful to work with independent component analysis (ICA), a technique that parses independent component (IC) signals from correlated time-series data. ICA of EEG is based on the premise that each electrode on the scalp records a linear sum of various underlying electrocortical signals, as well as electromyographic, electro-ocular, electrocardiographic, and movement artifacts. Thus, ICs representing neural activity or artifacts can now be separated from ICs representing artifacts [19].

In this study, we use a promising new method for analyzing EEG data in the context of music listening. Here, we apply the functional independent component (ICA) sLORETA approach. sLORETA provides a linear inverse solution method for reconstructing cortical electrical activity from scalp EEG data [20]. The implementation of ICA in this context allows for decomposition of cortical electrical activity into different and independent ICs within the intracortical space, representing networks of simultaneously activated and/or deactivated brain regions. Furthermore, sLORETA-ICA uses all frequency information of the EEG data for the analysis, thus efficiently identifying independent profiles of intracortical activation across all chosen frequency bands. Each sLORETA-IC represents a particular network and is expressed as one IC value. This allows for powerful statistical testing, as the huge amount of intracortical data is substantially reduced to a much smaller number. A further advantage of this technique is that artifact-contaminated ICs can easily be identified and eliminated from further analysis.

Using this promising new EEG analysis technique, we examine which brain areas are activated during music and scale listening compared with resting state. Using these stimulation paradigms in the context of the sLORETA-ICA, we examine the following questions. First, which networks are activated during listening to a musical piece compared with the resting and scale listening condition? The intention here is to identify the music-relevant networks and to compare the identified networks with those delineated in previous fMRI studies. Second, which music-activated network is the most dominant? This question has become possible to answer as the new sLORETA-ICA approach allows for quantification of the variance explained by a particular IC. Thus, the identified networks can be ranked according to the amount of explained variance. Third, which frequency bands contribute predominantly to the identified networks? Several studies have shown that each frequency band is related to particular neurophysiological and psychological processes [21–25].

Methods

Subjects

In total 34 German-speaking individuals (all from Switzerland) participated in this study. Three individuals were excluded because of left-handedness, alcohol abuse, or showing too many artifacts in the recorded data. The remaining 31 individuals (16 female) were right-handed, of normal hearing, demonstrated physical and psychological health at present and in the past, and were free from drug abuse. All participants were asked to refrain from drinking alcohol 24 h before the experiment. The mean age of the participants was 24 years (SD = 3.4). Sixteen participants were students of the Zurich music conservatory (Hochschule für Musik und Theater Zürich). In this study, we did not analyze potential differences between musicians and nonmusicians in terms of the identified neurophysiological activation patterns, as we were only interested in testing the feasibility of the sLORETA-IC approach for studying music-related neurophysiological activations. All participants were informed thoroughly about the method and the experimental procedure. They knew that they would be able to withdraw from the experiment anytime without having to provide any explanation. All participants provided informed written consent.

Experimental setup and procedure

The data presented here were taken from a larger experiment during which the participants were enrolled in different experimental settings. Here, we report only the results of three conditions (resting state with eyes closed: Rest; listening to music scales: Scale; and listening to a musical piece: Music). We have used four additional conditions (playing the musical piece with and without feedback, playing the musical scales with and without feedback) in this project. However, as we are only interested in reporting the sLORETA-ICA analysis in the context of music listening, we refrain from reporting the results of the other four conditions. During the Scale condition, the participants listened to five-tone scales from C′ to G′ and C′ to G′ played up and down on an electronic piano (YAMAHA P-60; *https://usa.yamaha.com/products/musical-instruments/keyboards/digitalpianos/p_series/p-60/*). These scales were recorded and played back using the software tool Cubase (*https://www.steinberg.net/de/products/cubase/start.html*). During the Music condition the participants listened to an excerpt of the first movement of the Sonata Facile composed by Wolfgang Amadeus Mozart (KV 545) played by Maria João Pires. During the experiment, the participants were sitting in front of the electronic piano (YAMAHA P-60) looking at the screen of the stimulation computer. At first, a resting EEG measurement was recorded. The participants were asked to close their eyes for 40 s and to leave them open for further 20 s. The two listening conditions (Scale and Music) lasted 30 s each and were repeated six times each. Thus, we obtained 180 s of EEG for the Scale and Music conditions. During all conditions, the participants were asked to look at a white fixation cross on a black background and to blink as rarely as possible, to minimize eye artifacts. During the listening conditions, they were asked to listen to the scales and to the music as relaxed as possible.

EEG recording

EEG was recorded using the QuickAmp-System (BrainProducts, Gilching, Germany). We used 32 silver-chloride electrodes that were fixed to the scalp according to the International 10–10 system using the BrainProducts caps (BrainAmp, BrainProducts, Germany). The EEG input signals were referenced to linked ears, filtered between 0.1 and 30 Hz, and digitized at a rate of 500 Hz. Frequencies higher than 30 Hz were eliminated to eliminate artifact-contaminated EEG. The ground electrode was placed on the forehead. All electrode impedances were kept below 10 kΩ. For artifact correction, a 50 Hz notch filter was used to remove network radiation. In addition, remaining muscular and eye artifacts were removed using the automatic raw data inspector of the Brainvision analyzer (BrainProducts, Germany).

EEG data preprocessing

For artifact-correction and preprocessing, Brainvision analyzer software was used. Artifact-contaminated epochs were automatically excluded from further analysis using ICA analysis and commonly used artifacts rejection thresholds (50 μV for Fp1 and Fp2 electrodes and 100 μV for other electrodes; 50 μV – for slow waves extracting using digital filtering in 0–1 Hz band; 35 μV – for fast waves filtered in the band 20–35 Hz [26,27]). For each participant, at least 140-s artifact-free segments for each condition were selected and used for further ICA analysis.

sLORETA analysis

Current density for each voxel was computed for seven EEG frequency bands established using factor analysis [28]: delta (1.5–6 Hz), theta (6.5–8 Hz), alpha-1 (8.5–10 Hz), alpha-2 (10.5–12 Hz), beta-1 (12.5–18 Hz), beta-2 (18.5–21 Hz), and beta-3 (22–30 Hz). We did not use the gamma band (>30 Hz), to avoid possible artifact contamination often seen in the gamma band. Technical details on the methods for computing the frequency domain cross-spectral matrices of cortical electric neuronal activity can be found in the study by Frei *et al.* [29]. sLORETA results consist of current density at each of 6239 cortical voxels (5 mm spatial resolution) in Montreal Neurological Institute space [30].

sLORETA-fICA

ICA methods are frequently used for the discovery of sets of regions that work together as networks. Here we use the term ‘network’ in a more broader and descriptive sense. The ‘networks’ we have identified are brain areas, which conjointly are activated and/or deactivated. In the following we describe and paraphrase the sLORETA-functional independent component analysis (fICA) method according to the description given in the paper of Aoki *et al.* [19]. The EEG recordings of each participant are first transformed to the frequency domain, resulting in a set of cross-spectral EEG matrices, for each frequency band and for each condition. On the basis of this information, the spectral density for each cortical voxel and for each frequency band is calculated using the methodology described in detail in the study by Frei *et al.* [29]. After this procedure, we obtained seven sLORETA images of cortical spectral density (one for each frequency band: delta, theta, alpha-1, alpha-2, beta-1, beta-2, and beta-3). In the next step, the data from each participant and condition are concatenated, thus producing a matrix where one dimension corresponds to the different participants and conditions, and the other dimension corresponds jointly to space frequency. The ICA is now applied to this matrix revealing different functional networks, each consisting of a set of seven images, one for each frequency, because space and frequency and all their possible interactions are now jointly expressed. These EEG-sLORETA-based functional networks correspond to brain regions and frequencies that ‘work’ together across a population of participants. This allows not only for the discovery of regions that work together but also for the discovery of cross-frequency couplings. A further advantage of this method is that for each network the amount of explained variance is calculated. Each network is represented by an IC coefficient, which can be used for further statistical analysis. We used these IC coefficients to test whether the ICs differ between the resting state (Rest), the scale listening condition (Scale), and the music listening condition (Music). These IC coefficients are also used for comparing the strength of the particular network between musicians and non-musicians. The obtained ICAs are then ranked according to total EEG power and color coded with a threshold of $z=3.0$, which is associated with $P=0.0027$. As we worked with 10 ICs, we used a Bonferroni–Holm correction [31] resulting in $P=0.0027\times10=0.027$. In the color-coded maps shown in the results section, red/yellow and blue represent power increases and decreases with increasing IC coefficient, which indicates activity of IC.

Results

The fICA analysis revealed several networks for the resting state, the scale listening, and the music listening conditions. These networks are similar for female and male participants. From the 10 ICs identified for Rest, one IC explained 98% of the variance. The remaining

Table 1 Percent of explained variance and the predominant frequency band separately for each network and for each condition

	Rest	Scale	Music
Network-1	98.05/Theta	62.62/Beta-2	62.71/Beta-3
Network-2	0.97/Alpha-2	13.37/Beta-3	12.68/Beta-3
Network-3	0.21/Beta-3	6.32/Beta-3	6.56/Beta-2
Network-4	0.13/Alpha-1	4.18/Beta-3	4.08/Beta-3
Network-5	0.11/Theta	2.32/Alpha-2	2.18/Alpha-2
Network-6	0.09/Alpha-2	1.72/Beta-3	1.90/Beta-3
Network-7	0.07/Beta-1	1.52/Delta	1.46/Beta-3
Network-8	0.06/Alpha-2	1.11/Alpha-1	1.32/Alpha-1
Network-9	0.05/Beta-3	1.00/Delta	0.97/Alpha-1
Network-10	0.04/Beta-3	0.76/Alpha-1	0.91/Alpha-2
%	≈100	≈95	≈95

ICs are less important for explaining the entire variance. For the sake of completeness, we have listed even these weaker ICs obtained for Rest in Table 1. For the Scale and Music listening conditions, the 10 ICs explained in total ~95% of the entire variance. The percent of explained variances as well as the predominant frequency bands separately for each condition are listed in Table 1. In the following we will describe each network in terms of the brain regions and the predominant frequency bands. For this, we descriptively chose the frequency band for which the particular IC demonstrates the maximum activity.

As one can see from Table 1, the predominant frequency bands for Scale and Music are mostly found for the fast frequency bands (beta-2 and beta-3), especially when considering those ICs explaining the largest amount of variance. For Rest, the maxima were found mainly in the theta and alpha frequency bands, especially for the IC explaining nearly the entire variance (IC-1) and IC-2 explaining ~1% of the variance.

The ICs for the three conditions are shown in Fig. 1. For Rest, IC-1 explains 98% of the entire variance. This IC comprises brain regions located in dorsomesial parts of the brain with predominant theta activity. This network includes frontal and parietal areas (with the precuneus). Nevertheless, there are also areas in the inferior parietal lobule and the temporo-occipital junction (TPJ) on the left hemisphere. However, the left-sided TPJ activity is anticorrelated with the activity in dorsal areas. Thus, when the mesiodorsal theta activity increases, the theta activity in the left-sided TPJ decreases. IC-2 of REST explains ~1% of the current density variance. The predominant frequency is the alpha-2 band. The involved brain areas are practically the same as for IC-1, with an anticorrelation between mesiodorsal alpha-2 and TPC alpha-2. All of the further ICs comprise brain areas in dorsomesial regions, however, with partly different predominant frequencies (beta-3: IC-3, IC-9, and IC-10; alpha-1: IC-4; theta: IC-5; beta-1: IC-7). Two of these less-prominent ICs also comprise activated brain areas in perisylvian brain regions (IC-5 and IC-8).

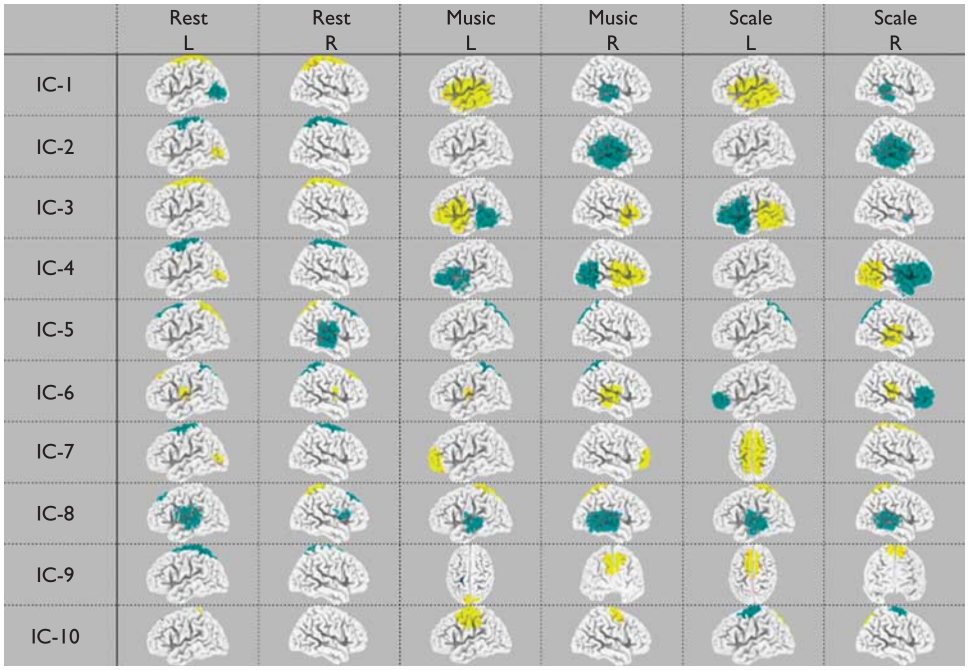
IC-1 and IC-2 are similar for the Scale and Music conditions. The predominant frequencies of these ICs are in the higher beta frequency and are located bilaterally in perisylvian regions. IC-1, which explains ~63% of the variance, reveals anticorrelated beta activity with increased activity in the left and decreased activity on the right side. IC-2 (explaining ~13% of the variance) is characterized by right-sided beta-3 band activity decreases. These perisylvian regions comprise primary and secondary auditory areas on the superior temporal gyrus (STG) as well as brain areas in the superior temporal sulcus (STS) and within the middle temporal gyrus (MTG). There are also current densities in the inferior frontal gyrus (IFG, Broca's area), the inferior parietal lobule (IPL), as well as in the inferior parts of the sensorimotor cortex.

IC-3 is different for the Scale and Music conditions. Most of the involved brain areas of these ICs are similar in both conditions; however, the current densities of the involved areas are differently anticorrelated for the scale and music listening conditions. During both conditions, the current densities were found in extended left-sided perisylvian brain regions comprising the IFG, the STS, the STG, the MTG, and also the inferior temporal gyrus. However, in the scale condition, the anterior perisylvian areas demonstrate decreased beta-3 current densities with increased beta-3 current densities in posterior perisylvian areas. For the music condition the anticorrelation is inverted with strong beta-3 current densities in the anterior left-sided and decreased beta-3 current densities in posterior perisylvian regions. Thus, although the same areas are involved, they are involved in a different manner. Beta-3 current densities are increased within the right anterior perisylvian brain during music listening, whereas there was only a relatively small spot in the right anterior perisylvian region with decreased beta-3 current densities.

IC-4 is also different for the Scale and Music conditions. For the Scale condition, we have identified a right-sided network for the beta-3 band with decreased current densities in anterior regions and increased current densities in posterior areas. The anterior regions comprise the IFG and anterior parts of the STG, STS, and the MTG. The posterior areas comprise posterior parts of the STG, the IPL, and occipital areas. There was no brain area in the left hemisphere being part of this network. For the Music condition the right-sided areas are the same as for the scale listening condition. However, we found strong differences for the left-sided areas with current density decreases in anterior areas comprising the IFG and the anterior part of the temporal cortex.

IC-5 is a network with a dominant frequency in the alpha-2 band. In the Scale and Music conditions there are current density decreases in brain areas comprising the

Fig. 1



Cortical localizations of the 10 intracortical independent components (IC-1 to IC-10) for resting state (Rest), music (Music), and scale (Scale) listening. The corresponding frequency bands are shown in Table 1. In the color–coded maps, red/yellow and blue colors represent power increase and decrease with increasing IC coefficient, respectively.

dorsal information stream with the precuneus and the superior parietal lobule. In the Scale condition, there is also an increase of current density in the right STG extending into the STS and MTG. Thus, the dorsal stream alpha-2 current density decrease is anticorrelated with the right-sided current density increase in the STG, STS, and MTG.

The next ICs (IC-6–IC-10) for the Scale and Music conditions explain in total only $\sim$6% of the entire variance. Thus, we will not describe them in detail here. The predominant frequency bands are in the delta, alpha-1, alpha-2, and beta-2 bands. The uncovered brain regions comprise perisylvian areas as well as mesial parietal and frontal areas. IC-6 and IC-8 stick out a bit. Both ICs show brain areas, which demonstrate anticorrelated activities between perisylvian and mesial–dorsal brain areas during the Scale and Music condition. During the Music condition, IC-6 is an IC with beta-3, as the predominant frequency band in which mesiodorsal parietal areas are deactivated, whereas perisylvian areas are activated. In the Scale condition, however, the perisylvian areas are rather less activated, whereas the frontopolar brain regions are activated. IC-10 is also an interesting network with alpha activation in the vicinity of the sensorimotor cortex during the Music condition and an alpha deactivation in the same area during the Scale condition.

Discussion

The scientific study of the neural underpinnings of music perception is a growing research area. Most studies published so far have used fMRI techniques to delineate the brain regions involved in music perception. However, because of the scanner noise and the uncomfortable scanner environment, fMRI measures are contaminated with many detrimental effects, including scanner-noise dependent artifacts and uncomfortable experimental conditions. Similarly, intracortical registrations in severely ill patients during music listening as have been conducted recently [32–34] are also associated with several detrimental effects (e.g. registration only in a relatively small brain area in one hemisphere, very obtrusive experimental condition). Thus, there is an urgent need for alternative techniques to delineate the brain regions involved in music listening, without disturbing and detrimental influences. One promising method is EEG, which can be measured in environments that are comfortable for the participants and, most importantly, are free from disturbing background noise.

The goal of this paper was to examine whether a new method for analyzing EEG data in the context of music listening is helpful for delineating the underlying neural networks active during music listening. Here, we used the newly developed functional independent component (ICA) sLORETA approach, which is a mathematical technique that allows the identification of intracerebral networks on the basis of scalp EEG measures [19]. The advantage of this technique is that the identified networks are represented across the different frequency bands. This allows the identification of the frequency bands that are most important for a particular IC, as well as the identification of the brain regions that are anticorrelated (e.g. one region is activated, whereas the other is deactivated). Using this technique, we identified several networks, particularly in the bilateral perisylvian areas, which are specifically activated when listening to a musical piece and scales. Thus, the identified networks comprise brain areas that are known to be strongly involved in complex auditory processing and music listening in particular [1,35].

The resting state networks, however, do not include the perisylvian brain areas. A further interesting finding is that the predominant frequency bands of the networks active during the Music and Scale conditions are in the beta-2 and beta-3 frequency bands, whereas most of the resting state networks operate in lower frequency bands (alpha-1, alpha-2, theta). Thus, during music and scale listening, entirely different networks are active, with entirely different predominant frequency bands compared with the resting state networks.

On comparing the networks obtained during the music and scale listening conditions, there are similarities but also differences. The differences are mainly found for the networks IC-3 to IC-5. For IC-3, we obtained increased beta-3 activity in the anterior left-sided perisylvian regions and decreased beta-3 current densities in the posterior left-sided perisylvian regions. While listening to scales, the same IC is active but the direction of anticorrelation is reversed. Thus, decreased beta-3 current densities in the anterior left-sided perisylvian areas are associated with increased beta-3 current densities in the posterior left-sided perisylvian regions. There are also further differences with respect to the networks obtained during music and scale listening for those ICs that only explain small percentages of variance (e.g. IC-6, IC-7, and IC-9).

The pivotal feature of the identified ICs is that they are mathematically independent. Thus, these networks most likely subserve different psychological functions during music and scale listening. The most prominent networks found for the music and scale listening conditions (IC-1–IC-5), which explain ~70% of the entire variance, comprise brain areas that are known to be important for auditory processing in general and music processing in particular. These areas are known to process basic auditory information (e.g. Heschl's gyrus), store and generate auditory images (STG, MTG, IPL), relate this auditory information to other modalities (STS), and process memory information (MTG and inferior temporal gyrus). Although not demonstrated in this study, we hypothesize that these networks are not simultaneously activated. We speculate that these different networks are sequentially activated, with one IC more prominently active during one period and another more prominently active during another period. It must be kept in mind that these networks were computed on the basis of EEG data measured during a relatively long period of time (3 min), during which the participants listened to music or scales. It is known that the brain changes its activation pattern approximately every 100 ms [36]. Thus, it could be possible that the network configuration also changes every 100 ms and that each of these networks use different processing modes while listening to music.

Although the differences between the resting state and music-scale-listening networks are obvious, it is worth discussing the differences between the networks identified for the music and scale listening conditions. During music listening, the anterior left-sided perisylvian areas are strongly activated, whereas the posterior areas are deactivated. This could indicate that during music listening, semantic perception or semantic categorization processes are activated, as these have been associated with left-sided activations in the IFG region [35]. Semantic processing during music listening has also been demonstrated in previous papers [37]. During scale listening, the anterior left-sided perisylvian brain area is deactivated, most likely because no semantic analysis is necessary during scale listening.

Some limitations are worthy of mention. First, we have calculated the fICAs for the entire period of listening to the musical piece and the scales, and thus we have neglected the time courses of brain activations during the auditory conditions. In addition, we did not focus on the possible relationship between particular acoustic features and the neural activations. However, future studies using more sophisticated analysis techniques combined with the fICA approach used here have to be developed to uncover possible time courses of neurophysiological activations. Second, we have applied sLORETA to infer and localize the underlying neural sources. Whether other methods for 'solving' the inverse solution provide similar or even better results has to be shown in future experiments.

Conclusion

Using a new mathematical approach to calculate intracortical ICs on the basis of scalp-recorded EEG, we have been able to delineate specific ICs for listening to a musical piece and scales. These ICs substantially differ from ICs calculated for the EEGs obtained during resting state. The ICs related to musical piece and scale listening comprise bilateral perisylvian brain areas, which are known to be involved in processing simple and complex auditory information. A further finding is that the musical piece and scale listening ICs are most prominent in higher frequency bands (e.g. beta-2 and beta-3), while the resting state ICs are active in lower frequency bands. Thus, the new technique of sLORETA-IC is able to delineate independent neural networks associated with music and scale listening. This tool therefore offers new opportunities for studying neural activations during music listening using the silent and more convenient EEG technology.

Acknowledgements

The authors thank Heidi König for acquiring the data, doing the artifact correction and segmentation. The authors also thank Susan Merillat for partly supervising the work of Heidi König. Data acquisition took place in 2006 as part of a Master thesis project.

Conflicts of interest

There are no conflicts of interest.

References

1 Trost W, Frühholz S, Cochrane T, Cojan Y, Vuilleumier P. Temporal dynamics of musical emotions examined through intersubject synchrony of brain activity. *Soc Cogn Affect Neurosci* 2015; **10**:1705–1721.

2 Montag C, Reuter M, Axmacher N. How one's favorite song activates the reward circuitry of the brain: personality matters. *Behav Brain Res* 2011; **225**:511–514.

3 Chapin H, Jantzen K, Kelso JA, Steinberg F, Large E. Dynamic emotional and neural responses to music depend on performance expression and listener experience. *PLoS One* 2010; **5**:e13812.

4 Chapin HL, Zanto T, Jantzen KJ, Kelso SJ, Steinberg F, Large EW. Neural responses to complex auditory rhythms: the role of attending. *Front Psychol* 2010; **1**:224.

5 Koelsch S, Skouras S, Jentschke S. Neural correlates of emotional personality: a structural and functional magnetic resonance imaging study. *PLoS One* 2013; **8**:e77196.

6 Baumgartner T, Lutz K, Schmidt CF, Jäncke L. The emotional power of music: how music enhances the feeling of affective pictures. *Brain Res* 2006; **1075**:151–164.

7 Lehne M, Rohrmeier M, Koelsch S. Tension-related activity in the orbitofrontal cortex and amygdala: an fMRI study with music. *Soc Cogn Affect Neurosci* 2014; **9**:1515–1523.

8 Lerner Y, Papo D, Zhdanov A, Belozersky L, Hendler T. Eyes wide shut: amygdala mediates eyes-closed effect on emotional experience with music. *PLoS One* 2009; **4**:e6230.

9 Mitterschiffthaler MT, Fu CH, Dalton JA, Andrew CM, Williams SC. A functional MRI study of happy and sad affective states induced by classical music. *Hum Brain Mapp* 2007; **28**:1150–1162.

10 Koelsch S, Fritz T, V Cramon DY, Müller K, Friederici AD. Investigating emotion with music: an fMRI study. *Hum Brain Mapp* 2006; **27**:239–250.

11 Herrmann CS, Oertel U, Wang Y, Maess B, Friederici AD. Noise affects auditory and linguistic processing differently: an MEG study. *Neuroreport* 2000; **11**:227–229.

12 Heinrich A, Szostek A, Meyer P, Reinhard I, Gilles M, Paslakis G, *et al.* Women are more strongly affected by dizziness in static magnetic fields of magnetic resonance imaging scanners. *Neuroreport* 2014; **25**:1081–1084.

13 Michel CM, Murray MM, Lantz G, Gonzalez S, Spinelli L, Grave de Peralta R. EEG source imaging. *Clin Neurophysiol* 2004; **115**:2195–2222.

14 Song J, Davey C, Poulsen C, Luu P, Turovets S, Anderson E, *et al.* EEG source localization: sensor density and head surface coverage. *J Neurosci Methods* 2015; **256**:9–21.

15 Zumsteg D, Wennberg RA, Treyer V, Buck A, Wieser HG. H_2(15)O or 13NH_3 PET and electromagnetic tomography (LORETA) during partial status epilepticus. *Neurology* 2005; **65**:1657–1660.

16 Zumsteg D, Friedman A, Wennberg RA, Wieser HG. Source localization of mesial temporal interictal epileptiform discharges: correlation with intracranial foramen ovale electrode recordings. *Clin Neurophysiol* 2005; **116**:2810–2818.

17 Zumsteg D, Lozano AM, Wennberg RA. Rhythmic cortical EEG synchronization with low frequency stimulation of the anterior and medial thalamus for epilepsy. *Clin Neurophysiol* 2006; **117**:2272–2278.

18 Zumsteg D, Friedman A, Wieser HG, Wennberg RA. Source localization of interictal epileptiform discharges: comparison of three different techniques to improve signal to noise ratio. *Clin Neurophysiol* 2006; **117**:562–571.

19 Aoki Y, Ishii R, Pascual-Marqui RD, Canuet L, Ikeda S, Hata M, *et al.* Detection of EEG-resting state independent networks by eLORETA-ICA method. *Front Hum Neurosci* 2015; **9**:31.

20 Pascual-Marqui RD. Standardized low-resolution brain electromagnetic tomography (sLORETA): technical details. *Methods Find Exp Clin Pharmacol* 2002; **24** (Suppl D):5–12.

21 Klimesch W. EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. *Brain Res Brain Res Rev* 1999; **29** (2–3):169–195.

22 Buzsáki G, Draguhn A. Neuronal oscillations in cortical networks. *Science* 2004; **304**:1926–1929.

23 Sammler D, Grigutsch M, Fritz T, Koelsch S. Music and emotion: electrophysiological correlates of the processing of pleasant and unpleasant music. *Psychophysiology* 2007; **44**:293–304.

24 Baumgartner T, Esslen M, Jäncke L. From emotion perception to emotion experience: emotions evoked by pictures and classical music. *Int J Psychophysiol* 2006; **60**:34–43.

25 Herrmann CS, Strüber D, Helfrich RF, Engel AK. EEG oscillations: from correlation to causality. *Int J Psychophysiol* 2015. [Epub ahead of print].

26 Ponomarev VA, Mueller A, Candrian G, Grin-Yatsenko VA, Kropotov JD. Group independent component analysis (gICA) and current source density (CSD) in the study of EEG in ADHD adults. *Clin Neurophysiol* 2014; **125**:83–97.

27 Alahmadi N. Classifying children with learning disabilities on the basis of resting state EEG measures using a linear discriminant analysis. *Z Neuropsychol* 2015; **26**:249–256.

28 Kubicki S, Herrmann WM, Fichte K, Freund G. Reflections on the topics: EEG frequency bands and regulation of vigilance. *Pharmakopsychiatr Neuropsychopharmakol* 1979; **12**:237–245.

29 Frei E, Gamma A, Pascual-Marqui R, Lehmann D, Hell D, Vollenweider FX. Localization of MDMA-induced brain activity in healthy volunteers using low resolution brain electromagnetic tomography (LORETA). *Hum Brain Mapp* 2001; **14**:152–165.

30 Evans AC, Collins DL, Mills SR, Brwon ED, Kelly RL, Peters TM. 3d statistical neuroanatomical models from 305 MRI volumes. Proceedings of IEEE Nuclear Science Symposium and Medical Imaging Conference. IEEE 3rd 1993; 1813-1817. Conference date: 31 Oct–6 Nov 1993.

31 Holm S. A simple sequentially rejective multiple test procedure. *Scand J Stat* 1979; **6**:65–70.

32 Sturm I, Blankertz B, Potes C, Schalk G, Curio G. ECoG high gamma activity reveals distinct cortical representations of lyrics passages, harmonic and timbre-related changes in a rock song. *Front Hum Neurosci* 2014; **8**:798.

33 Omigie D, Dellacherie D, Hasboun D, George N, Clement S, Baulac M, *et al.* An intracranial EEG study of the neural dynamics of musical valence processing. *Cereb Cortex* 2015; **25**:4038–4047.

34 Omigie D, Dellacherie D, Hasboun D, Clément S, Baulac M, Adam C, Samson S. Intracranial markers of emotional valence processing and judgments in music. *Cogn Neurosci* 2015; **6**:16–23.

35 Noesselt T, Shah NJ, Jäncke L. Top-down and bottom-up modulation of language related areas – an fMRI study. *BMC Neurosci* 2003; **4**:13.

36 Koenig T, Prichep L, Lehmann D, Sosa PV, Braeker E, Kleinlogel H, *et al.* Millisecond by millisecond, year by year: normative EEG microstates and developmental stages. *Neuroimage* 2002; **16**:41–48.

37 Koelsch S. Neural substrates of processing syntax and semantics in music. *Curr Opin Neurobiol* 2005; **15**:207–212.